Does Finance Flow to High Productivity Firms?*

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Abstract

This paper studies the impact of productivity on the flow of financial resources to and from firms. To do this we use machine learning methods (Lasso, XGBoost) to derive a new measure of firm productivity using standard corporate accounts. Output is sales revenue and we find that the key inputs are i) cost of goods sold, ii) selling general and administrative expenses, iii) total assets. Empirically finance typically flows away from high productivity firms. We provide a model to explain this evidenced based on the interactions between investors and firms, in response to transitory productivity shocks.

Keywords: productivity, capital structure, financing constraints, machine learning
JEL classification: D24, E23, G32

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1 Introduction

This paper is a study of the connection between corporate productivity and the flow of financial resources. It is widely recognized that efficient resource allocation is among the most important tasks for the financial system.[1] Investors are expected to invest in firms with positive net present value opportunities, and these projects ought to be more common at high productivity firms. So it seems plausible that external financial resources must flow to the more productive firms. However, investors provide funds to firms in anticipation of subsequent returns. So there may be a tension if high productivity is transitory. The firm should invest promptly to take advantage of the transitory opportunity, but the investors discount the future and so they want their investment returns relatively promptly as well. A priori it is not clear how this tension is resolved. The purpose of this paper is to document the related facts, and then provide an explanation for the evidence.

In order to do this we first need to determine which firms are more productive. This is challenging because our question is at the firm level, but most research on productivity is carried out at the plant level, see Griliches and Mairesse (1998) and Syverson (2011). In order to determine which firms are more productive, we use machine learning techniques (XGBoost and the Lasso) to develop and validate a novel firm level measure of productivity using ordinary corporate accounts. With output defined as sales revenue, we find that the key inputs in order of impact are: 1) cost of goods sold (COGS), 2) selling general and administrative expenses (SGA), and 3) total assets. After estimating the three factor model we follow the Solow residual approach and measure which firms have unusually high sales revenue given the observed spending on inputs. That defines our firm level measure of productivity. This productivity measure is easy to implement at the firm level, easy to interpret, and relates naturally to other firm attributes.

Using our new productivity measure, we then answer the paper title question. The answer is: no, finance does not generally flow to high productivity firms. On average finance flows away from high productivity firms, not towards them. As far as we know, this fact is new to the literature. This fact is empirically robust, and it has persisted over several decades.

[1] There is a huge literature on this topic including Demirgüç-Kunt and Levine (1996), La Porta et al. (1997), Rajan and Zingales (1998), Wurgler (2000), Hsieh and Klenow (2009), and Whited and Zhao (2017).

So it deserves an explanation.

The final part of the paper provides a simple model that can explain the direction of financial resource flow. The key idea in the model is that at times of high transitory productivity, due to discounting investors want some extra consumption now. However, to exploit a transitory opportunity the firm needs to acquire extra productive capital quickly. For both of these to happen at the same time, in the model the firm draws down on accumulated internal financial resources. This idea can account for several critical facts including most importantly, the direction of financial resource flows. We also provide direct evidence supporting the basic model mechanism. Firms really do draw down on internal financial resources when productivity is high.

Since it is new and crucial to our paper, we examine the performance of our productivity measurement in some detail. When high and low productivity firms are compared, high productivity firms tend to be smaller. Very high and very low productivity firms grow more rapidly than do moderate productivity firms. For empirically relevant values there is rather limited substitutability among the three inputs. Productivity is less widely dispersed across firms than usually thought. Firms that are bankrupt or liquidated generally had much lower than average productivity in the previous few years. Firms that are acquired or merged had higher than average productivity. Firms with more volatile productivity invest more and make more active use of financial markets.

Related Literature. There is a literature on capital reallocation as reviewed by Eisfeldt and Shi (2018). Much of the focus in that literature is concerned with the business cycle properties, aggregation and often focuses on plant level data, eg. Midrigan and Xu (2014). Our focus is on firms and our method of measuring firm level productivity is new. Maksimovic and Phillips (2001) show that individual plants are generally sold by firms that are relatively inefficient, and bought by firms that are relatively efficient. Foster et al. (2008) show that low productivity manufacturing plants are more likely to exit. However at the firm level Zingales (1998) finds that trucking firm productivity was less crucial than leverage for determining firm survival after the Carter trucking deregulation. Lee et al. (2018) find that after 1996 equity no longer flows to high Tobin's q industries. They attribute the change to several factors including equity repurchases, intangible assets and the impact of China. Eisfeldt and Rampini (2006) provide evidence that the amount of capital reallocation is procyclical. Eisfeldt and Muir (2016) point to corporate savings as an important element aspect of the process. This is an idea that we also consider to be important. Almeida and Campello (2007) points to the importance of financing constraints in this process. Whited and Zhao (2017) examine whether debt and equity appear to be efficiently allocated using a method similar to Hsieh and Klenow (2009). They do not focus on the interactions between real productivity and finance. The existing literature does not provide direct evidence about whether finance typically flows to more productive publicly traded firms.

The literature on productivity is huge and often at the plant level using Census Bureau data, see Syverson (2011) and Foster et al. (2017). At the firm level we know of productivity studies by İmrohoroğlu and Tüzel (2014), David and Venkateswaran (2017), De Loecker and Eeckhout (2017). Our paper is quite different from these studies due to our method of measuring firm productivity and our interest in financial flows. We are the first to apply machine learning methods to measuring firm productivity. So both the justification and our proposed three factor model of productivity are new. The measure does behave empirically in a manner consistent with it actually being a measure of firm productivity.

It is worth observing that much of the literature studying plant level productivity has focused on alternative ways of controlling for endogeneity using specialized data sets, see Olley and Pakes (1996), Griliches and Mairesse (1998), Levinsohn and Petrin (2003), Ackerberg et al. (2015), and many others. However, the evidence that controlling for endogeneity is really a first order empirical concern when measuring productivity is somewhat unclear, see Gandhi et al. (forthcoming). In our view, the choice of inputs, robustness, and external validity of the estimates are potentially as important considerations. The theory used to justify the methods of correcting for endogeneity may not be robust, see Ackerberg (2016). Empirically important factors may have been omitted resulting in biased inferences if the intercept is not sufficient to capture their effects. It has also resulted in many productivity studies avoiding firm level data. Major exceptions are İmrohoroğlu and Tüzel (2014) and David and Venkateswaran (2017), neither of which attempt the sort of exercise that this paper undertakes.

2 Firm Level Data

The data is from Compustat. This is the standard dataset providing the corporate accounts of publicly traded American firms. While this is widely used for many purposes in corporate finance, it has not been as widely used in studies of productivity. Because our question is at the firm level we must directly face the question of how best to use the available corporate accounts to evaluate corporate productivity.

We start with the Compustat data from 1950 to 2015 which contains 286,095 observations. We remove firms that are not incorporated in the USA, financial firms and regulated firms, duplicate observations, data from before 1972, cases in which the market leverage is less than 0.05, firms with missing identifiers or assets, and cases in which there are not at least 10 years of leverage information. Finally, we drop observations in 1971 because capital at 1972 is defined as the inflation-adjusted ppegt at 1971. This gives us the cleaned data with 102,747 firm-year observations. We partition this data into 90% that is for training ($91,584$ observations) and 10% that is for testing ($10,747$ observations). The impact of each step in the data cleaning is available in the appendix as Table 11.

The term productivity is defined here as the amount of sales revenue in excess of what is predicted based on the observed inputs. This is a straight forward application of the Solow residual perspective. To implement this we must define the inputs. We measure things in dollar terms not physical terms. This makes sense in that investors presumably care about money. We start with sales revenue as the measure of output and use the machine learning methods to determine the inputs from the corporate accounts. Once we have the estimate of productivity, we verify that the firm actions are consistent with the measure actually reflecting productivity.

Our approach is a sharp departure from the previous literature which assumes that capital and labor are the inputs. Such an assumption has been critiqued by Griliches and Mairesse (1998) due to the fact that both capital nor labor are conceptual aggregates rather than precisely defined measures. They also observe that standard approaches to measure these concepts result in econometric estimates that are problematic. Motivated by these observations we take a reverse perspective. We use the machine learning methods to ask, what directly measured aspects of the firm's spending seem to do a good job of accounting for sales revenue. We define these as inputs. We use those as variables in a conventional regression and take the residual as our definition of productivity.

2.1 Traditional Production Functions

The standard approach to estimating productivity is to have output as a function of capital and labor. Some papers measure these in physical units, and other papers measure these in dollar terms. Despite the long tradition and common use of capital and labor as 'the inputs', these are simply convenient aggregates. As observed by Griliches and Mairesse (1998): "our theories ... deal with reasonably crude aggregates: output, labor, capital which turn out to be rather vague concepts when we go down to the micro level."

Ordinary corporate accounts are measured in dollar terms, not physical units; and they do not break out labor separately. Capital is also not directly recorded. Since labor costs are not directly provided in the data, studies such as İmrohoroğlu and Tüzel (2014) multiply the firm's reported number of employees by an 'average wage' from the Social Security Administration. Since some firms pay more than others, this may be a concern since we are interested in obtaining firm-specific productivity.

Capital is commonly inferred from property plant and equipment, either directly or adjusted. Sometimes it is adjusted for inflation, or for mergers. Some studies use a perpetual inventory method along with a depreciation assumption, to construct an alternative measure of capital. There are issues about how to treat other assets including intangible capital and inventories. A review of the measurement of capital is provided by Hulten (1991).

Some studies estimate what they call a 'value added production function'. This approach categorizes some inputs as 'primary inputs' (capital and labor), while other inputs are deemed 'intermediate inputs' (materials). Ordinary corporate accounts do not provide a direct measure of materials. So it must again be calculated from things that are reported. İmrohoroğlu and Tüzel (2014) define it to be total expenses minus estimated labor expenses. They define total expenses to be sales minus operating income before depreciation and amortization.

Carrying out such 'value added' calculations is not hard, but is it appropriate? This depends on how managers and investors conceive of the firm's problem. It certainly does not match the manner in which accountants measure the firm. If these were really the key elements for corporate decision making, it is a bit surprising that standard accounting conventions have not adapted to provide information in the form needed by decision makers. Despite reservations, we have tried using a value added approach and it generates very similar results. To save space we do not report that.

Our major concern about the classical production production estimation is that: 1) as observed by Griliches and Mairesse (1998) it produces results that have drawbacks, 2) it rests on very specialized assumptions, 3) it ignores much of the actual assets and costs that real firms incur. This may be why most productivity studies analyze plant rather than firms.

For benchmarking purposes we first estimate traditional production functions using firm data. Then we study an alternative way to make use of the available data. There is a long tradition of estimating total factor productivity (productivity) as the residual of a Cobb Douglas function in which output depends on capital and labor, see Syverson (2011), İmrohoroğlu and Tüzel (2014), David and Venkateswaran (2017) and De Loecker and Eeckhout (2017). We also use the residual.

Including firm fixed effects seems natural, e.g. Mundlak (1961), Blundell and Bond (2000) and Gormley and Matsa (2013). But, as stressed by Griliches and Mairesse (1998) and Ackerberg et al. (2015), when this is done, the estimated coefficient on capital is implausibly low as is the implied returns to scale. To deal with this problem the literature has focused on developing alternative econometric methods that have a tight theoretical interpretation. But no consensus method has emerged, as reflected in studies such as Olley and Pakes (1996), Levinsohn and Petrin (2003), Wooldridge (2009), Ackerberg et al. (2015) and Collard-Wexler and De Loecker (2017). Generally these method are used to study particularly convenient datasets such as Chilean or Mexican plant level data rather than on publicly traded American firms.

Table 1 provides productivity estimates using several well known estimation methods. These include OLS, panel data, and two control function methods. Firm and year fixed effects are included in the panel, but empirically they are not important. Results without the fixed effects are included in the online appendix. The results in this Table are similar to those reported in previous studies. Based on macroeconomic time series data, it is often thought that the coefficient on capital is about 1/3 while the coefficient on labor is about 2/3. Using aggregate data from 1899 to 1922 Cobb and Douglas (1928) estimate that the coefficient on capital is 1/4 and on labor they find 3/4. There is some evidence that the coefficient on labor has been drifting down a bit in recent decades.

Column 1 reports results estimated using ordinary least squares. The coefficient on capital is 0.414 and the coefficient on labor is 0.566. In each case the standard errors are rather small. The R^2 is 0.883 suggesting that the model fits pretty well. This makes sense if you look at Figure 1.

The plots in Figure 1 show firm-average values of capital versus output, and labor versus output. All three values have been logged before plotting. In both cases a 45 degree line is plotted for reference. Both of these inputs scale strongly with output. In each case the center of the data mass is a bit above the line. Labor in particular seems to follow a steeper path than the 45 degree line. As labor increases by a unit output seems to increase by more than a unit. The plots help explain why the fixed effects seem relatively unimportant.

Column 2 of Table 1 redoes the estimation from column 1 but all variables are in first differences. Wooldridge (2010) points out that if the assumptions that justify estimating column 1 are correct, then the coefficients estimated in column 2 ought to have the same numerical values apart from minor variation due to end point effects. It is easy to see that equality of the coefficients in columns 1 and 2 is strongly rejected. Instead the coefficients are less than half as large. This means that despite the high R^2 in column 1, the model is not trustworthy.

Is the model in column 2 more reliable? Wooldridge (2010) suggests testing the first difference specification by adding the levels of the variables as regressors. The coefficients on the level variables ought to be zero. The results of such a test are provided in column 3. The levels of the variables are statistically significantly different from zero and the R^2 increases from 0.106 to 0.112. This calls equation 2 into question as well.

There is a long tradition of carrying out fixed effects productivity regressions, see Mundlak (1961). Following Blundell and Bond (2000) we use panel GMM regressions with lagged output as a regressor in column 4. In this case the coefficient on capital is actually negative. This has been a known issue with fixed effect productivity regressions as stressed by Griliches

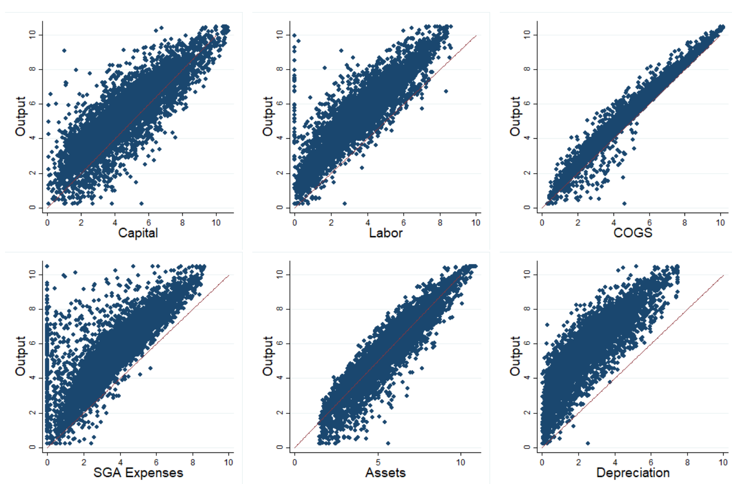
Table 1: Conventional Production Function Estimation

This table presents results of production function estimation for the training sample of firms from 1972 to 2015. Production function is in standard Cobb Douglas form, with capital and labor as input variables. Output is measured as sales. Capital is measured using gross property, plant, and equipment (PPEGT) deflated by price deflator for investment following İmrohoroğlu and Tüzel (2014). Labor is calculated by multiplying the number of employees from Compustat (EMP) by average wages from the Social Security Administration. The model is estimated using OLS, dynamic panel regression, control function methods Olley and Pakes (1996), and adjusted control function method Ackerberg et al. (2015) (denoted ACF). Column 2 represent OLS regression of all variables in first differences, column 3 adds input level as additional control variables. Column 4 represents panel GMM regression following Blundell and Bond (2000) with lagged output as a regressor. Column 5 and 6 report control function methods estimated coefficients on capital and labor. Capital is state variable, labor is freely variable input, and investment (measured as capital expenditure from Compustat) is proxy control. Estimations include year and 2-digit SIC industry fixed effects. A few observations are lost due to variables lagging at the beginning of the sample.

	(1) OLS	(2) OLS First Diff	(3) OLS First Diff	(4) Dynamic Panel	(5) Olley Pakes	(6) ACF
	Year and Industry Fixed Effects					
Capital	0.414		-0.029	-0.100	0.323	0.317
	(0.028)		(0.004)	(0.005)	(0.042)	(0.000)
Labor	0.566		0.029	0.227	0.623	0.706
	(0.028)		(0.004)	(0.004)	(0.014)	(0.000)
ΔCapital		0.119	0.124			
		(0.012)	(0.012)			
ΔLabor		0.211	0.192			
		(0.017)	(0.017)			
L.Output				0.759		
				(0.006)		
Observations	91584	91584	91584	86331	87835	87835
R^2	0.883	0.106	0.112			

Figure 1: Output and the Factors

This figure shows the plot of firm average output against capital, labor, COGS, SGA, depreciation and total assets. Output is measured as sales. Capital is measured using gross property, plant, and equipment (PPEGT) deflated by price deflator for investment following İmrohoroğlu and Tüzel (2014). Labor is calculated by multiplying the number of employees from Compustat (EMP) by average wages from the Social Security Administration. COGS, SGA, depreciation and total assets are directly from Compustat. For each firm, average output, capital, labor, COGS, SGA and total assets are calculated as equal weighted mean from 1972 to 2015. All variables are logged.



and Hausman (1986) and Griliches and Mairesse (1998). Column 4 shows that the difficulty has not gone away over time. As they stress, the estimated returns to scale seem implausibly low, further calling the approach into question.[2]

Motivated by the difficulty with panel regressions to estimate production function the literature has focused on trying to control for the endogeneity of the choices of capital and labor. The use of control functions starts with Olley and Pakes (1996) and continues with particularly important contributions by Levinsohn and Petrin (2003) and Ackerberg et al. (2015). We used Stata code written by Mollisi and Rovigatti (2017) to do the control function estimation. It is assumed that capital is the state variable, the free variable is labor and the proxy variable is investment.

In columns 5 and 6 we see that using control function methods the estimated coefficients on capital and labor are reasonably close to those estimated in column 1. The estimated coefficients on capital are lower and those on labor are higher.

Are the estimates in Table 1 credible? The literature has done a good job establishing that such methods work under the structural assumption being invoked. They have been used on firm level data by İmrohoroğlu and Tüzel (2014) and David and Venkateswaran (2017). But little is known about the external validity of the methods. Given the direct evidence of problems in columns 2, 3 and 4, consistent we Griliches and Mairesse (1998), we are not confident in the results generated by such traditional production functions. Following Olley and Pakes (1996), much of the literature has made tight theoretical assumptions to justify alternative estimation methods to resolve this problem. We do not follow that approach. As a matter of theory Ackerberg (2016) and Gandhi et al. (forthcoming) show that the estimation methods can be quite sensitive to timing and informational assumptions. There is little solid evidence on these theoretically crucial issues. So we lack confidence in those methods. Furthermore these methods do not fit naturally with firm level data, since they ignore a great deal of money flows are real firms as reflected in the ordinary corporate accounts.

[2] We tried using past stock market returns as an instrument, but we dropped the idea. Our initial experiments produced results that were not robust. This seems consistent with the concerns in Jiang (2017). Even more worryingly Young (2017) shows that IV methods seem to frequently generate fragile inferences, even in well done studies published in top journals.

3 Measuring Firm Productivity

The traditional methods as in Table 1 ignore most of the corporate accounts. Those accounts, while imperfect, do provide a window on what firms are really doing. An obvious thing to do is to use more information from the corporate accounts. But what to add from the accounts?

In order to answer this question we turn to empirical methods that have proven to be successful in the machine learning literature, see Efron and Hastie (2016). Two algorithms have been particularly prominent for somewhat analogous problems. One is known as the Lasso and it is originally due to Tibshirani (1996). The version of the Lasso that we use was proposed by Belloni et al. (2012). The other machine learning method we use is known as Gradient Boosting. We use the very successful software called XGBoost which due to Chen and Guestrin (2016).

3.1 Selecting Factors

The first step is to partition the data into a training sample that contains 90% of the data, and a testing sample that contains 10% of the data. Except where specifically indicated, our reported results are for the the training data. The testing data is to assess the estimates in a pseudo-out-of-sample setting.

The second step is to define the candidate input variables. From the balance sheet any asset recorded with a $+$ is a candidate. Any variable in the income statement recorded with a $-$ is also a candidate. We also include labor, year, and 2-digit sic industrial dummies, as candidate inputs. The third step in selecting the factors is to use the machine learning methods.

The Lasso. This is a penalized regression method. Let y_i denote the output for observation i, x_i is the vector of inputs, n is the number of observations, β are the coefficients to be estimated. Following Belloni et al. (2012), the Lasso solves the following problem.

The Stata code we used to implement the method is for a version called Lasso Shooting and we use the code provided by Hansen.[3] The details are based on Belloni et al. (2012).

[3] http://faculty.chicagobooth.edu/christian.hansen/research/

For a helpful discussion of the approach see Belloni et al. (2014).

$$\widehat{\beta} = \arg\min_{b} \sum_{i=1}^{n} (y_i - \sum_{j=1}^{p} x_{i,j} b_j)^2 + \lambda \sum_{j=1}^{p} |b_j| \gamma_j \tag{1}$$

Regularization is controlled by the penalty level λ. The Lasso Shooting algorithm ex-ante sets $\lambda = 2.2 * \sqrt{(2 * n * log(2 * p/(.1/log(n))))}$, where p is number of variables and n is the number of observation. This balances overfitting and bias. Coefficient specific penalty loadings are controlled by γ. Ex-ante we do not have a fixed γ, but rely on data-dependent penalty loading procedure, which introduces self-normalization of the first-order condition of the lasso problem.

In Table 2 for the Lasso we report the actual parameter estimates. Note that the Lasso penalizes nonzero values, so some shrinkage of the coefficients towards zero might be expected even for the coefficients that are optimally nonzero. We report results for all of the training data as well as separate results for manufacturing firms and non-manufacturing firms. Most of the the candidate inputs are set equal to zero and hence not reported in the Table. COGS, SGA, total assets and labor are deemed to be significantly nonzero in all three columns. Depreciation matters for all firms and for non-manufacturing, but it does not survive for the manufacturing firms. There is also some support for interest expenses and equity investment. For the other variables the coefficients are numerically close to zero and they seem inconsistent from one column to the next.

Gradient Boosting. This is based on an ensemble of trees. The main idea is to start by estimating a decision tree of a fixed shallow depth. For that tree the residuals are computed. At the next iteration more weight is devoted to the cases in which the model fit poorly. In the end an ensemble of trees are used to 'vote' on the appropriate results. We use the popular verison known as XGBoost (Extreme Gradient Boosting) Chen and Guestrin (2016). This is among the most successful supervised machine learning algorithms currently available. This approach has proved extremely successful in practice on a large number of applied problems. To save space we do not go over the technique in detail here. We use the Scikit-Learn interface for XGBoost in python using the default parameters setting. Maximum tree depth for base learners is 3, Boosting learning rate is 0.1 and Number of boosted trees to fit is 100.

With Gradient Boosting we again provide results for all firms, manufacturing firms, and non-manufacturing firms. The reported values are called 'feature importance' and they report how often in the forest of trees, the indicated variable proved to be an important factor. We keep variables with a feature importance of above 30, and we also report some added feature importance values.

Overall Choice of Factors. It is clear that the COGS, SGA and total asset belong in any reasonable empirical model. That gives 3 core factors. Depreciation and Labor are more marginal. In Table 2 they have lower significance. Beyond these variables, another variable of note is interest expense. Like depreciation it was also important for all firms under the Lasso. But in this case the feature important values are much smaller under XGBoost. So this might argue for dropping the variable. Perhaps more importantly, we view the interest expense is part of the financing of the firm. Furthermore it is also taken into account as part of the COGS. So we exclude it from the basic model.

In Table 3 the final column shows what happens when the five factors (depreciation and labor added) are included in a regression. While the standard errors might suggest their inclusion, they add essentially nothing to the ability to explain the data. Not surprisingly, they make essentially no difference to subsequent results either. Accordingly we adopted the more parsimonious 3 factor model as the base case model.

Figure 1 shows how the factors relate to output. Each factor is plotted against output. Each dot is a firm average. All variables are logged. For reference 45 degree lines are included. All factors scale strongly with output. The tightest connection is obviously with COGS. Labor, SGA and especially depreciation all increase more rapidly than the 45 degree line. The strength of the correlations might cause concern about multicollinearity. However, our sample size is large and when first differenced the correlations among the factors are all below 0.5. Empirically, we did not find any evidence of a multicollinearity problem.

3.2 Productivity Estimation With Three Factors

There are two natural approaches to estimating firm productivity using the three factors. One approach is to use the output of the ML algorithms directly. This has a potential advantage of greater efficiency. The other approach is to use the three factors as factors in

Table 2: Which Inputs Matter?

This table presents production function estimation for the training sample of firms from 1972 to 2015, using machine learning algorithm Lasso and XGBoost. Manuf means manufacturing firms. The Lasso and XGBoost algorithm are applied to predict output, which is measured as sales. The variables capital, labor, and other variables cogs, xsga, dp, xint, mii, ppent, ivaeq, ivao, intan and at from firms' balance sheets and income statements are alternative explanatory variables. In the Lasso case, the lasso estimated coefficients of algorithm selected variables are provided. In XGBoost estimates, feature importances are provided for variables with feature importances larger than 10. Estimates are controlled with both time and 2-digit SIC industry fixed effects. The estimates using the whole training sample, manufacturing firms, and non-manufacturing firms are provided separately. Variable definitions can be found in appendix A.

	Lasso			XGBoost		
	All	Manuf	Non-Manuf Firms	All	Manuf Firms	Non-Manuf Firms
COGS	0.708	0.697	0.716	221	234	223
SGA	0.110	0.195	0.069	154	198	115
Total Assets	0.166	0.114	0.178	57	53	54
Depreciation	0.067		0.091	53	10	64
Labor	0.019	0.027	0.008	37	41	54
Interest Expense	-0.016	-0.005	-0.012	15	22	15
Equity Investment	-0.012	-0.006	-0.009	<10	<10	<10
Other Investment		0.002		10	17	10
Intangible Assets		0.006	-0.003	<10	13	<10
Net PPE		0.016		12	10	14
Minority Interest	0.003			16	14	22

Table 3: Production Functions Estimated with Three Factors

This table presents results of production function estimation from 1972 to 2015. Production function is estimated using three factor model, with COGS, SGA and total assets as input variables. Output is measured as sales. The model is estimated using OLS, and dynamic panel regression. Column 2 represents OLS regression of all variables in first differences, column 3 adds levels of input variables as additional control variables. Column 4 represents panel GMM regressions following Blundell and Bond (2000). Column 5 and 6 are OLS regressions with only COGS and additional variables. Time and 2-digit SIC industry fixed effects are included. COGS, SGA, total assets and depreciation are directly from Compustat. Labor is calculated by multiplying the number of employees from Compustat (EMP) by average wages from the Social Security Administration.

	OLS	OLS First Diff	OLS First Diff	Dynamic Panel	OLS	OLS
COGS	0.729	0.732	0.732	0.749	0.991	0.709
	(0.028)	(0.053)	(0.054)	(0.002)	(0.009)	(0.032)
SGA	0.122	0.161	0.162	0.139		0.115
	(0.035)	(0.037)	(0.037)	(0.001)		(0.033)
Total Assets	0.196	0.160	0.159	0.122		0.151
	(0.021)	(0.032)	(0.033)	(0.003)		(0.016)
Depreciation						0.059
						(0.016)
Labor						0.022
						(0.014)
Add Variable Level		No	Yes			
Observations	91584	91584	91584	86331	91584	91584
R^2	0.978	0.750	0.750	0.978	0.965	0.978

a regression. This has a potential advantage of easier interpretation. We have used both approaches and the end results are essentially the same. So we focus on the three factor regression residuals, which we call productivity.

Table 3 is similar to Table 1 except that in this case we use the three factors instead of capital and labor. The reported results include industry and year fixed effects. But the presence or absence of fixed effects proved empirically unimportant. Column 1 of Table 3 reports simple OLS results. We calculate variance inflation factor (VIF) for the regressions, it turns out that total assets has VIF 12, which is the only variable with VIF larger than 10, the regular threshold to evaluate multicollinearity. So overall, we believe that multicollinearity is not a big issue here. This is strengthened by the similarity of coefficients when estimated in first difference.

The productivity model fits the data very well, with an $\overline{R}^2 = 0.978$. The high $\overline{R}^2$ is perhaps not so surprising due to the high correlation between COGS and output (0.981). The coefficients on each of the factors is statistically significant at conventional levels. Not surprisingly the significance and magnitude of the coefficient on COGS is particularly strong. Column 2 is the same model but estimated in first differences. We are interested in the stability of the estimated coefficients. The estimated coefficients are very similar in columns 1 and 2. A natural test of the model in column 2 is to reintroduce the variables in levels along with the first differences. In column 3 we find that the $\overline{R}^2$ is 0.750 in both columns and the parameters are also quite stable. This is supportive of the appropriateness of the specification in column 2. For comparison recall Table 1 where we report the results of first difference estimation for a capital and labor model. In first differences fell sharply to $\overline{R}^2 = 0.106$, and the estimated coefficients dropped sharply. In column 4 of Table 3 use panel GMM estimation. The coefficients on the three variables are only minimally affected. This model does not suffer from the parameter magnitude and returns to scale problems that worried Griliches and Mairesse (1998).

Due to the empirical importance of COGS we also report a univariate regression in column 5. The univariate coefficient on COGS is 0.991 (S.E. 0.009) with an $\overline{R}^2 = 0.965$. The returns are again close to constant. So COGS is doing most of the work. But the model is not quite as good as the three factor model including SGA and TA. In column 6 we find that including factors beyond these three seems rather unimportant.

To recap. All three of the factors are empirically robust and economically reasonable. The model measures the extent to which a firm generates sales revenue in excess of what is expected based on the resources it uses. The COGS and SGA include a variety of productive inputs include labor services that are used by the firm as flow variables. These are used up in the period. Total assets is a measure of the full stock of resources that the firm holds. All of these assets have an opportunity cost and may depreciate. This three factor model reflects much more of what the firm is doing, in contrast to a traditional capital and labor model. A firm that can generate a great deal of sales revenue from these inputs we call a high productivity firm.

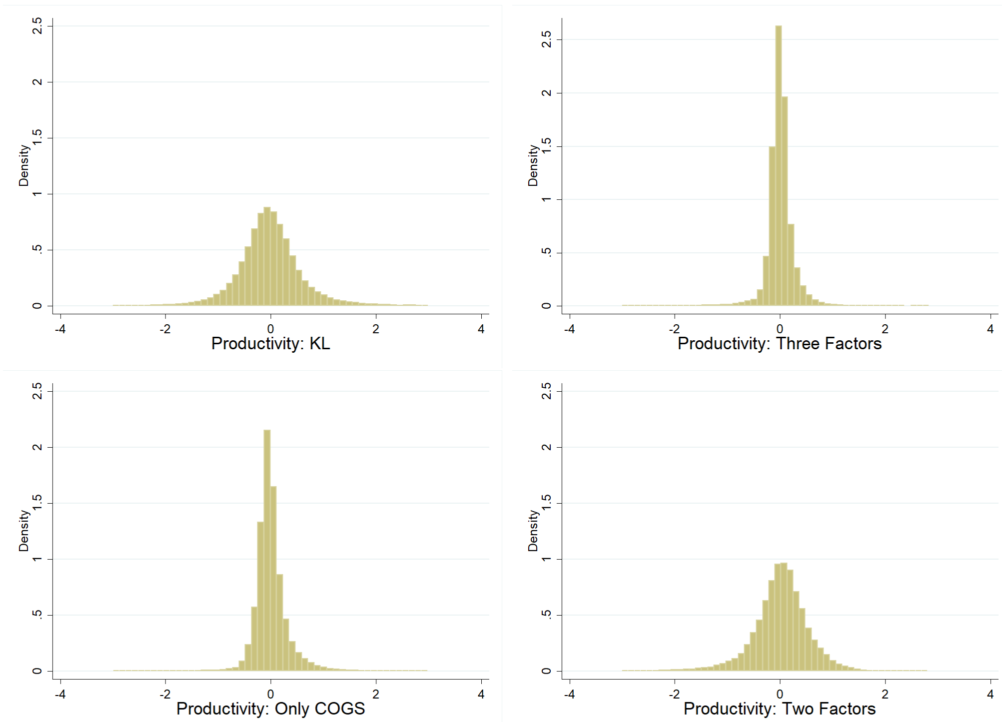
4 Understanding Three Factor Firm Productivity

In this section we explore the three factor productivity model in order to clarify what the model says about the nature of firm productivity. Does the new measure relate to firm decisions in a reasonable manner? This is important due to the novelty of our three factor model. We consider some basic statistical properties of the model. Then we examine how productivity relates to the reasons for firm exit reported by Compustat. Next, we compare a variety of firm attributes for high and low productivity firms. After that we compare firms with highly variable productivity to firms with lower variability.

The single more important factor is COGS, and it's impact is illustrated in Figure 2. Each panel displays the dispersion of productivity under a particular model. In the upper left hand panel the dispersion of productivity derived from a conventional model. Next to it is the corresponding density plot for the three factor model. Under the three factors there is dramatically less dispersion. In the second row on the left hand side we provide the density plot for the 1 factor COGS model. It is almost as narrow as the full three factor model plot. Next to it we provide a plot for the density of a model that starts with the three factors but excludes COGS. As can be easily seen it is a much more dispersed plot than even the single factor COGS. Indeed it is only somewhat less dispersed than the KL model. So COGS itself is playing the key role in narrowing the dispersion.

Figure 2: Dispersion of Productivity

This figure shows the dispersion of different productivity measures. Histograms of different productivity measures are plotted for Compustat firms from 1972 to 2015. Productivity is measured as OLS residuals from regressing sales on different factors and controlling for year and 2-digit SIC industry fixed effects. Factors include: capital and labor (KL); COGS, SGA and total assets; only COGS; SGA and total assets (Two Factors).



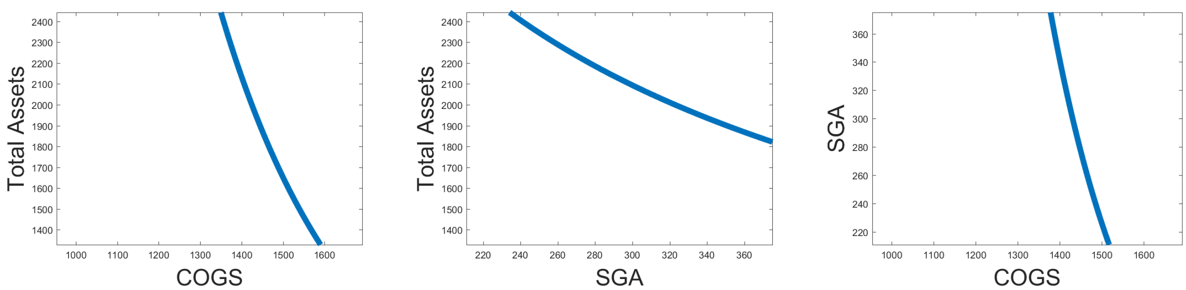
In the existing literature an accepted fact is that productivity dispersion across firms is large and persistent, see Syverson (2011). Figure 2 shows genuine dispersion across firms as well. However, the dispersion using our three factor model is much lower than suggested by traditional models. Some of the usual dispersion may simply be a measurement issue reflecting omitted inputs.

How much scope for substitution is there among these three factors? To answer this Figure 3 plots isoquants for the three factors holding the other factors at the mean value. The plots cover much of the observed range of observed data values.

There is not a great deal of convexity. In most cases it takes a very large increase of one factor to compensate for a unit reduction of another factor. For example it takes a huge increase in total assets to compensate for even a small reduction in the COGS. If we go

Figure 3: Empirical isoquants for three factors model

This figure shows the plot of empirical isoquants for 3 factors production function. Production function is estimated using three factor model, with COGS, SGA and total assets as input variables. Output is measured as sales. For each isoquant, we move only two variables and keep the other variables at its mean. The scales of x-axis and y-axis are drawn from mean - 0.1*std.dev. to mean + 0.1*std.dev.



very far from the mean, the models suggest greater substitutability. But that often happens far outside the observed range of actual firm decisions. So considerable caution is needed regarding such estimates.

It is well known that there are highly persistent differences in productivity across plants, see Syverson (2011). Is this also true across firms under the three factor model? To answer this question we estimated firm-specific AR(1) models. Figure 4 plots the distribution of estimated persistence parameters. There is a high degree of persistence in general. There is a significant skewness to the distribution indicating that for some firms there is much less persistence than for others. This result is true both using a traditional KL model and using our three factor model.

4.1 Productivity and Reasons for Exit

If resources are to be efficiently allocated, then low productivity firms should either improve productivity or exit. In this subsection we examine the empirical connection between productivity and the reason for exit. Table 4 shows the productivity measure for the firms that exit. In each case we provide the average productivity in the final year for which we have data (year 0) as will as for the 2 prior years.

The patterns are straight forward. Firms that exit due to a merger or an acquisition have

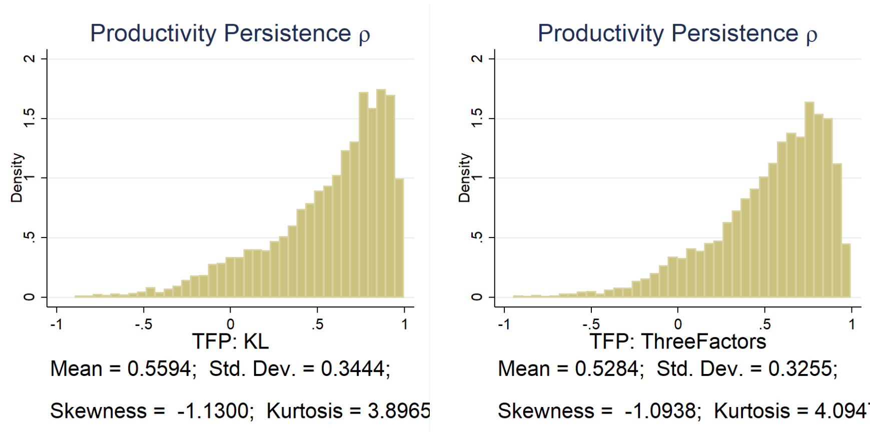
Table 4: Productivity and Reasons For Exit

The table provides a time series change of productivity for firms with different Compustat deletion codes. Companies can exit in various ways. Compustat footnote 35 provides evidence on the relative importance of alternative exit mechanisms. The firms are sorted by the last year in Compustat Data, which is defined as the difference between year deletion from Compustat and current fiscal year. Productivity is measured as OLS residuals from regressing sales on three factors and controlling for year and 2-digit SIC industry fixed effects. Three factors are COGS, SGA and total assets. We take the simple average of productivity for firms with same deletion code and same year from Deletion. Observations give the raw count of the number of firms with the particular reason for deletion.

	Last Year:	0	-1	-2
Acquisition or merger	productivity	0.039	0.031	0.028
	observations	2610	2597	2580
Now a private company	productivity	0.002	-0.019	-0.013
	observations	172	172	171
Leveraged buyout	productivity	0.010	0.005	0.000
	observations	43	43	43
Liquidation	productivity	-0.141	-0.067	-0.056
(chapter 7)	observations	121	120	119
Bankruptcy	productivity	-0.074	-0.045	-0.019
(chapter 11)	observations	227	226	223
Reverse acquisition	productivity	-0.133	-0.272	-0.221
(from 1983 onward)	observations	32	32	31
No longer fits original format	productivity	-0.054	-0.026	-0.038
(1978 forward)	observations	2	2	2
Other	productivity	-0.136	-0.098	-0.076
(no longer files with SEC etc.)	observations	539	532	527
Other	productivity	-0.104	-0.076	-0.040
(no longer files with SEC etc.)	observations	247	246	245
(but pricing continues)				

Figure 4: Firm Level Productivity Persistence

This figure shows the persistence of firm-level productivity. Histograms of firm-level productivity persistence are plotted. Productivity is measured as OLS residuals from regressing sales on different factors and controlling for year and 2-digit SIC industry fixed effects. Sets of factors include: (1) capital and labor (KL); (2) COGS, SGA and total assets. For each firm i, we fit a AR(1) model, $z_{i,t} = \rho_i z_{i,t-1} + \varepsilon_{it}$, and firm level productivity persistence is measured as estimated ρ_i.



above average productivity. Firms that are still operating but which became private have slightly above average productivity in the final year but had been below average previously. These may be recovering firms in some sense. We do not have many LBOs (only 43), but those that we do observe have slightly above average productivity.

Firms that liquidate (chapter 7) or that are bankrupt (chapter 11) have below average productivity. We also observe a tiny number of reverse acquisitions. In a reverse acquisition a private firm buys a public firm in order to become public without going through the expense of an IPO. Firms that are acquired for that purpose are few in number and they have very low productivity. There are a series of 'other' categories that are harder to interpret. These are generally associated with low productivity.

The evidence in 4 is reassuring. It makes sense that liquidated firms have low productivity, and the other categories also seem reasonable. Firms that cease operating typically have low productivity.

Table 5: How Do High and Low Productivity Firms Differ?

This table presents the summary statistics of firm characteristics from 1972 to 2015. Each year, firms are sorted into quintiles evenly, by their contemporaneous productivity, which is measured using OLS residuals from regressing sales on three factors and controlling for year and 2-digit SIC industry fixed effects. Three factors are COGS, SGA and total assets. All variable definitions can be found in the appendix A. Summary statistics for the Hoberg and Maksimovic (2015) financing constraint measure from 1997 to 2015 are also provided.

Productivity Average	Low		Medium		High
	1	2	3	4	5
Productivity: Three Factors	-0.351	-0.073	0.005	0.087	0.332
Logged Variables					
Sales	5.786	6.299	5.755	5.239	5.452
Capital	5.591	5.531	4.888	4.312	4.743
Labor	4.249	4.601	4.030	3.472	3.498
COGS	5.617	5.953	5.382	4.807	4.701
SGA	4.222	4.505	3.973	3.466	3.001
Total Assets	6.309	6.135	5.463	4.897	5.406
Scaled Variables					
Investment (CAPX)/PPEGT	0.103	0.093	0.093	0.099	0.116
Investment (Cash Flow)/Assets	0.107	0.106	0.094	0.095	0.129
Cash/Assets	0.145	0.090	0.092	0.105	0.134
Net Cash/Assets	-0.193	-0.076	0.001	0.057	-0.037
Net Finance/Assets	0.121	0.041	0.021	0.013	0.017
Net Finance (Issuance)/Assets	0.131	0.053	0.033	0.026	0.035
Other Variables					
Dividend	0.541	0.582	0.531	0.480	0.524
Tobin Q	3.938	1.893	1.700	2.013	3.947
Market to Book	1.345	1.061	1.108	1.220	1.609
Tangibility	0.323	0.314	0.306	0.298	0.334
Profitability	-0.013	0.099	0.120	0.140	0.171
Book Leverage	0.316	0.290	0.266	0.243	0.244
Market Leverage	0.363	0.349	0.317	0.276	0.249
Growth of Assets	13.823	8.448	7.192	7.749	11.866
observations	20484	20467	20461	20467	20452
Financing Constraint 1997-2015					
"Delay Investment"	0.004	-0.026	-0.033	-0.037	-0.017
Observations	6443	6513	6650	6670	6587

4.2 High and Low Average Productivity

This subsection provides information about how high productivity firms differ from low productivity firms on average. Table 5 sorts firms into quintiles based on 3 factor productivity, and then provides a number of descriptive statistics for each quintile. In the online Appendix we provide a corresponding table in which we directly use the XGBoost based productivity measure. The patterns are generally similar. In Table 5 the residual based productivity ranges from -0.351 in the lowest quintile to 0.332 in the top quintile.

The first group of measures are for variables in logs. The results are not purely monotonic across the quintiles. The general sense is that low productivity firms tend to be somewhat larger than high productivity firms, but it depends on exactly which measure of size is used. For example the largest sales are in the second quintile (6.299) while the largest assets are in the first quintile (6.309).

The second group of measures are scaled by total assets. These provide data descriptions that control for a basic measure of firm size. There is a very clear U-shaped pattern. Investment is higher in the first and fifth quintiles than for moderate productivity firms. The extremes also hold more cash relative to assets. According to Denis and Sibilkov (2009) financially constrained firms that expect to invest hold more cash, which roughly matches this evidence. The extreme quintiles have negative net cash which together with the cash result, implies that they have greater debt. The net use of external finance is sharply concentrated in the lowest productivity quintile (0.131).

The third set of descriptive statistics provide common firm attributes. Several of these are consistent with greater investment at both extremes. Both Tobin's q and the Market-to-book are higher in the first and fifth quintiles than in the middle. The growth of assets is also clearly U-shaped. Profitability is monotonic increasing in productivity as might be expected. Leverage is monotonic decreasing in productivity.

In the on-line Appendix we provide similar tables for NBER recession years and for normal years separately. The basic patterns are fairly similar. Not surprising, there is less investment during recessions. There is also much less net financing. Interestingly across all quintiles, dividends and leverage are both somewhat higher during recessions while Tobin's

Q is lower.

4.3 Productivity Variability

Table 6 provides the same set of descriptive statistics is in table 5. The difference is that the quintiles are now based on the firm level conditional standard deviation of productivity. We assume firm level productivity follows an AR(1) process, $z_{it} = \rho_i z_{i,t-1} + \varepsilon_{it}$, where $\varepsilon_{it} \sim N(0, \sigma_i^2)$. For each firm, we fit a productivity AR(1) model to estimate the parameters $\{\rho_i, \sigma_i^2\}$. Productivity variability is defined to be the conditional standard deviation σ_i^2, which is not the unconditional measure $\sqrt{\frac{\sigma_i^2}{1-\rho_i^2}}$. When we refer to productivity volatility, we mean conditional volatility unless otherwise indicated. So quintile 1 are firms with very little productivity variability ($\sigma_i = 0.023$) and quintile 5 contains firms with extremely high variable productivity ($\sigma_i = 0.303$).

The top group of variables show stark size effects. Low productivity variability firms are larger across all measures, and the patterns are monotonic. The variables that are scaled by total assets are again monotonic across the productivity variability quintiles. Investment is greater in the high productivity variability quintile. That same group of firms holds more cash. They issue more. Since these quintiles are defined by productivity volatility it seems that the quintile firms are facing much more variable problems, and so they adjust more.

The other measures present a similar general picture. Quintile 5 firms have higher market-to-book, higher Tobin's q, and much higher growth of assets. While they have slightly higher book leverage, market leverage is quite constant across these quintiles. Profitability is higher in the lowest productivity volatility quintile. These are the firms that are least likely to report being financially constrained.

The measures reported so far are simple descriptive statics. They are broadly similar to Almeida et al. (2004), Almeida and Campello (2007) and Denis and Sibilkov (2009), although we focus more on firm productivity than on financing constraints. Firms invest when they have good opportunities. They use the resources that they have on hand or they may raise outside finance. If they are concerned about their ability to access outside capital they hold more cash in order to prepare. The investment opportunities are greater among both the very high productivity and the very low productivity than among the more moderate

Table 6: Productivity Variability

This table presents the summary statistics of firm characteristics from 1972 to 2015. For each firm i, we fit an AR(1) model, $z_{i,t} = \rho_i z_{i,t-1} + \varepsilon_{it}$, where $\varepsilon_{it} \sim N(0, \sigma_i^2)$. Firm level productivity variability is estimated as σ_i, which is the conditional standard deviation of firm productivity shock. Firms are sorted into quintiles based on the productivity variability. Average σ_i reported is the productivity conditional standard deviation for firm i averaged across firms in the quintile. All variable definitions can be found in the appendix A. Summary statistics for the Hoberg and Maksimovic (2015) financing constraint measure for from 1997 to 2015 are also provided.

Productivity Variability	Low 1	2	Medium 3	4	High 5
Average σ_i	0.023	0.037	0.055	0.095	0.303
Logged Variables					
Sales	6.810	6.233	5.618	5.238	4.457
Capital	5.819	5.415	4.853	4.556	4.312
Labor	5.072	4.534	3.873	3.456	2.738
COGS	6.454	5.848	5.191	4.749	4.040
SGA	4.959	4.306	3.791	3.282	2.664
Total Assets	6.299	5.930	5.449	5.314	5.142
Scaled Variables					
Investment (CAPX)/PPEGT	0.081	0.087	0.096	0.113	0.132
Investment (Cash Flow)/Assets	0.088	0.091	0.097	0.114	0.148
Cash/Assets	0.071	0.085	0.101	0.135	0.185
Net Cash/Assets	0.010	-0.012	-0.023	-0.063	-0.178
Net Finance/Assets	-0.007	0.002	0.018	0.050	0.167
Net Finance (Issuance)/Assets	0.012	0.017	0.032	0.061	0.174
Other Variables					
Dividend	0.744	0.616	0.492	0.400	0.382
Tobin Q	1.092	1.506	1.938	3.333	6.163
Market to Book	1.052	1.080	1.161	1.331	1.789
Tangibility	0.320	0.315	0.302	0.295	0.346
Profitability	0.152	0.140	0.121	0.093	-0.004
Book Leverage	0.246	0.254	0.270	0.280	0.316
Market Leverage	0.310	0.315	0.314	0.308	0.306
Growth of Assets	4.984	6.102	7.449	11.855	20.168
Observations	20491	22405	20787	20100	18548
Financing Constraint 1997-2015					
"Delay Investment"	-0.038	-0.035	-0.031	-0.022	0.012
Observations	5414	6810	6824	6888	6927

productivity firms. To go further it is important to consider how productivity fits when other variables are also included.

5 Productivity and Firm Decisions

In this section we study decisions by firms as a function of productivity. First we examine real investment. Then we consider the use of external finance. Finally we consider the connection to internal cash holdings.

5.1 Real Investment

High productivity firms ought to invest more. However, under classical conditions Tobin's q is a sufficient statistic for the incentive invest, as in Hayashi (1982). If q is included in a regression there will be nothing left for productivity to account for. Empirically, measured q can never be so perfect, so including productivity in an investment regression is of interest. There is an extensive literature on investment that has generally been critical of ordinary q, see Fazzari et al. (1988), Erickson and Whited (2000), Frank and Shen (2016). Andrei et al. (forthcoming) show that q theory works well in recent decades, and this good performance is driven in large part by an increase in volatility.

This subsection studies the same approach as in Andrei et al. (forthcoming) but with our 3 factor productivity measure as an added regressor. The results are reported in Table 7. Consistent with Andrei et al. (forthcoming), column 1 shows that lagged q is empirically significant. However, when productivity is included as a regressor, the magnitude of the coefficient on q is closer to zero.

The impact of the 3 factor productivity measure on investment is statistically significant and it is not subsumed by q. Columns 2 through 5 sort firms grouped on the volatility of Tobin's q as in Table 1 of Andrei et al. (forthcoming). Productivity is much more important for low Tobin's q volatility firms than for the high volatility firms.

Recall that Andrei et al. (forthcoming) find that high volatility is helpful to the efficacy of Tobin's q. Our columns 2 though 5 suggest that productivity plays a complementary role. It works best for firms that q works less well. Columns 5 and 6 distinguish non-high tech

Table 7: Does Productivity Affect Investment?

This table performs panel regressions of investment on lagged Tobin's q and productivity from 1972 to 2015. Investment rate and Tobin's q are constructed following Andrei et al. (forthcoming). Productivity is measured using OLS residuals from regressing sales on three factors and controlling for year and 2-digit SIC industry fixed effects. Three factors include COGS, SGA and total assets. In the first column, the analysis is conducted in full sample. From column 2 to column 5, firms are sorted into 4 bins based on within-firm volatility of Tobin's q, with Bin 1 as the lowest volatility group. In the column 6 and column 7, firms are grouped into high-tech and low-tech firms. "HighT" (high tech) refers to SIC codes 283, 357, 366, 367,382, 384, and 737. Standard errors are clustered at firm level, and within firm R^2 is reported. "L." is the one-period lag operator.

		Group by within firm volatility of q				Group by Industry	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Invt.	Invt.	Invt.	Invt.	Invt.	Invt.	Invt.
L.Tobin q	0.006***	0.044***	0.026***	0.016***	0.006***	0.006***	0.006***
	(0.000)	(0.002)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)
Productivity	0.011**	0.011**	0.017**	0.010	0.005	0.021***	-0.004
	(0.005)	(0.005)	(0.008)	(0.009)	(0.009)	(0.005)	(0.009)
Productivity^2	0.000	-0.013**	-0.013*	-0.006	0.000	0.004	-0.004
	(0.003)	(0.005)	(0.007)	(0.008)	(0.004)	(0.004)	(0.004)
Sample	All Firms	Bin 1	Bin 2	Bin 3	Bin 4	Non-HighT	HighT
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Within R^2	0.100	0.055	0.070	0.093	0.149	0.075	0.156
Observations	95578	23823	24105	24112	23538	75276	20302

Standard errors in parentheses.

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

and high tech firms. Productivity is very important for the non-high tech firms, but it is not statistically significant for the high tech firms.

The overall message in Table 7 simple. High productivity firms do invest more, even conditioning on Tobin's q. Tobin's q is particularly important for high q volatility and high tech firms. Productivity is particularly important for low q volatility and non-high tech firms. For our purposes the key point is the simple fact that when a firm has high productivity it really does invest more on average. This is a key part of the mechanism developed in our model in section 6.

5.2 External Finance

In this section we study the connection between three factor productivity and firm financing. There are three aspects that we examine: the use of external finance, the presence or absence of a financing constraint, the use of internal financial resources commonly called 'cash'.

Table 8 examines the impact of productivity on net external financing. There are several possible definitions of net financing. The data is from Compustat. In columns 1 and 2, Net Finance = FINCF/ AT_{t-1} This is from the firm's statement of cash flows. In column 4 a similar measure is constructed by hand from the debt and equity transactions.

The key message in Table 8 is shown in the first row. High productivity firms have negative net finance - not positive. On average they are returning funds to investors, not getting more financing. This effect is robust to variation in the way we measure external financing. It is quite robust to alternative control variables. It is not subsumed by firm 'profitability'. Indeed the profitability control actually strengthens the point. More profitable firms also have negative net finance, as do firms with more assets. On the other hand high market-to-book firms have positive net finance.

So far we have found that more productive firms generally make payments to the financial markets instead of raising funds from the markets. They do not raise much outside funding on average. Similar evidence has been found with respect to dividends. Denis and Osobov (2008) found that more profitable firms pay more dividends. We have documented in Table 5 that productivity and profitability are positively correlated.

What about high productivity firms that actually need the money? What do they do?

Table 8: Do High Productivity Firms Raise More External Finance?

This table presents regression results of external financing on productivity and financial constraint. Productivity is measured using OLS residuals from regressing sales on three factors and controlling for year and 2-digit SIC industry fixed effects. Three factors include COGS, SGA and total assets. Net Finance = FINCF/ AT_{t-1}, Net Finance(Issuance) = (DLTIS - DLTR + DLCCH + SSTK - PRSTKC)/ AT_{t-1}, and Net Finance(DivAdj) = (DLTIS - DLTR + DLCCH + SSTK - PRSTKC - DV)/ AT_{t-1}. Financing constraint is measured using textual based financing constraint measure "delay investment" from Hoberg and Maksimovic (2015). Sample in column (1) consists firms from 1972 to 2015. Sample in other columns consists firms from 1997 to 2015. Frank and Goyal (2009) factors, year and 2-digit SIC industry fixed effects are included. All variable definitions can be found in the appendix A. "L." is the one-period lag operator

	(1) Net Finance	(2) Net Finance	(3) Net Finance (DivAdj)	(4) Net Finance (Issuance)
Productivity	-0.103***	-0.118***	-0.119***	-0.114***
	(0.008)	(0.018)	(0.017)	(0.017)
Productivity^2	0.011***	-0.005	-0.006	-0.004
	(0.004)	(0.009)	(0.008)	(0.008)
L.Market to Book	0.074***	0.068***	0.066***	0.067***
	(0.001)	(0.003)	(0.003)	(0.003)
L.Tangibility	0.046***	0.013	0.014	0.010
	(0.012)	(0.032)	(0.031)	(0.031)
L.Profitability	-0.446***	-0.526***	-0.518***	-0.500***
	(0.013)	(0.029)	(0.028)	(0.028)
L.Assets	-0.015***	-0.021***	-0.019***	-0.020***
	(0.001)	(0.003)	(0.003)	(0.003)
L.Dividend	0.002	-0.005	-0.007	0.011
	(0.004)	(0.012)	(0.011)	(0.011)
Financing Constraint		0.115*	0.112*	0.117*
		(0.063)	(0.060)	(0.060)
Productivity*Financing Constraint		-0.179	-0.200	-0.207*
		(0.130)	(0.125)	(0.126)
Industry Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	96422	31915	31915	31915
R^2	0.078	0.066	0.068	0.067

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

To answer this question we need to identify the firms that need money. We use the 'delay investment' measure from Hoberg and Maksimovic (2015) to measure firms in need of money. These are firms that have indicated that they are delaying investment due to financing issues. The measure is based on the discussions of management in corporate reports. The linguistic approach has the added advantage that it does not use the same data as the productivity measures.

We find that firms that are financially constrained have positive net finance but the effect is fairly weak. The interaction between productivity and financing constraints is also very weak.

5.3 Cash Holding

The idea that cash holding can be used in preparation for financial frictions has been developed by Almeida et al. (2004), Almeida and Campello (2007) and Denis and Sibilkov (2009) among others. Therefore we examine the connection to productivity, since productivity is related to the benefits to investing. Table 7 shows that on average high productivity firms invest more. Table 8 shows that on average high productivity firms send money to investors. So where does the money to pay for the investment come from? The obvious idea is that the firm uses internal financial resources, i.e. cash. Table 9 examines this possibility. Denis and Sibilkov (2009) show that financially constrained firms hold more cash to avoid having their investment disrupted.

We consider two definitions of cash: 'current assets' (ACT) is a broad notion of cash, 'cash and short-term investments' (CHE) is a somewhat narrower conception. Columns 1 and 2 use the narrower definition while columns 3 and 4 use the broader definition. Columns 2 and 4 include measures of financing constraints while columns 1 and 3 do not. The basic message is in the first row. High productivity firms keep less cash on hand. This effect is more pronounced for the narrower definition of cash, and in column 4 the effect is not statistically significant. This suggests that the narrower definition provides the better characterization of cash as the readily useful internal financial resources. It is of interest to see that profitability has a negative sign for the narrower definition but a positive sign for the broader definition. This again seems to suggest that the narrower definition is more appropriate.

Table 9: Do High Productivity Firms Hold More Cash?

This table presents regression results of cash holding and net csah holding on productivity and financial constraint. Productivity is measured using OLS residuals from regressing sales on three factors and controlling for year and 2-digit SIC industry fixed effects. Three factors include COGS, SGA and total assets. Using Compustat definitions, Cash = CHE/ AT_{t-1} and Net Cash = (ACT - LT)/ AT_{t-1}. Financing constraint is measured using textual based financing constraint measure "delay investment" from Hoberg and Maksimovic (2015). Sample in column (1) (3) consists firms from 1972 to 2015. Sample in column (2) (4) consists firms from 1997 to 2015. Frank and Goyal (2009) factors, year and 2-digit SIC industry fixed effects are included. All variable definitions can be founds in the appendix. "L." is the one-period lag operator

	(1) Cash	(2) Cash	(3) Net Cash	(4) Net Cash
Productivity	-0.038***	-0.050***	-0.021**	-0.022
	(0.005)	(0.011)	(0.008)	(0.017)
Productivity^2	0.035***	0.009*	0.038***	0.015*
	(0.002)	(0.005)	(0.004)	(0.008)
L.Market to Book	0.083***	0.110***	-0.017***	-0.048***
	(0.001)	(0.002)	(0.001)	(0.003)
L.Tangibility	-0.179***	-0.214***	-0.579***	-0.546***
	(0.007)	(0.019)	(0.012)	(0.030)
L.Profitability	-0.149***	-0.160***	0.531***	0.552***
	(0.008)	(0.017)	(0.014)	(0.027)
L.Assets	-0.010***	-0.015***	-0.059***	-0.079***
	(0.001)	(0.002)	(0.001)	(0.003)
L.Dividend	-0.007***	-0.026***	0.025***	-0.003
	(0.003)	(0.007)	(0.005)	(0.011)
Financing Constraint		0.109***		0.125**
		(0.037)		(0.059)
Productivity*Financing Constraint		-0.304***		-0.898***
		(0.077)		(0.122)
Industry Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Observations	96422	31915	96422	31915
R^2	0.162	0.185	0.152	0.114

Standard errors in parentheses

$^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$

Consistent with Almeida and Campello (2007) and Denis and Sibilkov (2009), financially constrained firms hold more cash. But financially constrained firms that are high productivity have less cash. Overall, this evidence is consistent with the idea that high productivity firms do draw down their cash to use in other ways when needed.

6 Model

The empirical work has shown that more productive firms 1) invest more in real assets, 2) return financial resources to investors, and 3) have lower internal cash holding. The purpose of the model is to show that these key facts fit together naturally. Accordingly many simplifications are adopted in order to highlight the main mechanism, even when that means that some moments do not fit the data as precisely.

6.1 Investor

It is well known, that investors are typically not well diversified, see Goetzmann and Kumar (2008). There are a range of idea about the reason for inadequate diversification. For our purposes the key point is that due to a lack of diversification, even idiosyncratic shocks to the firm are not fully diversified away by the investor. That idea is captured simply in the model by the fact that the only financial product available to the investor is from the firm.

The investor has preferences over consumption plans that are valued according to

$$E_0 \sum_{t=0}^{\infty} \beta^t u(c_t) \tag{2}$$

where E_t is the expectation conditional on date t information, c_t is the date t consumption, u is the strictly concave single period utility function, and $\beta \in (0, 1)$ is the discount factor. When an explicit functional from of utility is needed, we assume that $u(c) = \frac{c^{1-\gamma}}{1-\gamma}$, where $\gamma > 0$. As a result $u_c = c^{-\gamma}$.

The investor maximizes (2) by choosing a plan for consumption and investing in the firm shares $\{c_t, s_{t+1}\}_{t=0}^{\infty}$, subject to a sequence of budget constraints

$$s_t(d_t + p_t) = c_t + s_{t+1}p_t,\ t \geq 0 \tag{3}$$

where s_{t+1} is the number of shares, d_t is the per share divided, p_t is the price of the shares. There is also initial condition on s_0. We let $\beta^t \lambda_t$ denote the date-specific Lagrange multiplier on the budget constraint.

The first order conditions with respect to c_t, and s_{t+1} are given by,

$$c_t : u_c(c_t) - \lambda_t = 0 \tag{4}$$

$$s_{t+1} : -\lambda_t p_t + E_t \beta \lambda_{t+1}(d_{t+1} + p_{t+1}) = 0 \tag{5}$$

These conditions can be used to solve out the Lagrange multipliers. Then repeated forward substitution of the price gives the price of shares,

$$p_t = E_t \sum_{j=1}^{\infty} (\beta^j \frac{u_c(c_{t+j})}{u_c(c_t)}) d_{t+j}.$$

The term $m_{t+j} = \beta^j \frac{\lambda_{t+j}}{\lambda_t}$ is the stochastic discount factor. It expresses how the investor values cash at different dates.

6.2 Firm

The firm objective function is defined as the expected discounted flow of dividends d_t, using the investor's stochastic discount factor.

$$E_0 \sum_{t=1}^{\infty} m_t d_t \tag{6}$$

The firm maximizes (6) by choosing a plan for the bank account, dividends, physical capital and capital investment $\{b_{t+1}, d_t, k_{t+1}, i_t\}_{t=0}^{\infty}$, subject to the sequence of flow budget constraints. The firm's flow budget says the firm obtains resources from operations, from leftover physical capital and as a return on the bank account. The firm uses resources to finance capital investment, to pay capital adjustment cost $\Phi(i_t, k_t)$, to deposit in the bank and to pay dividends. It is given by,

$$F_t(k_t) + (1 + r_t)b_t = i_t + \Phi(i_t, k_t) + b_{t+1} + d_t,\ t \geq 0 \tag{7}$$

the law of motion of capital is given by,

$$k_{t+1} = i_t + (1 - \delta)k_t \tag{8}$$

with $\delta \in (0, 1)$. The capital adjustment cost is convex, given by

$$\Phi(i_t, k_t) = \frac{a}{2}(\frac{i_t}{k_t})^2 k_t \tag{9}$$

There are also initial conditions on $\{k_0, b_0, z_0\}$. For simplicity the number of firm shares is normalized as $s_t = 1$ for all t. $\beta^t \xi_t$ is the date specific the Lagrange multiplier associated with budget constraint, and $\beta^t q_t$ is the Lagrange multiplier associated with law of motion for capital.

Production is given by $F_t(k_t) = e^{z_t} A k_t^{\alpha}$, with $A > 0$, $\alpha \in (0, 1)$, e is Euler's number, $\rho_z \in (0, 1)$, and

$$z_t = \rho_z z_{t-1} + \varepsilon_t,\ \varepsilon_t \sim N(0, \sigma_z^2) \text{ iid.} \tag{10}$$

The firm has access to a bank account with an effective return of

$$r_t = r_f - \omega b_t. \tag{11}$$

The risk free rate $r_f \in (0, 1)$ is exogenously determined. The term $\omega > 0$ measures the interest sensitivity to the amount that the firm deposits in the bank b_t. The idea that corporate savings/bank account is important for understanding external financial flows is not new, e.g. see Eisfeldt and Muir (2016). The idea underlying (11) is based on Jensen (1986). As the bank deposit grows in size the more important it becomes for the firm be able to show that it has done proper due diligence. This creates an opportunity for empire building inside the firm that is costly and that grows with the size of the account. This interpretation of

ω appeals to us, but opinions may differ. Alternative theoretical justifications that generate an interior solution require more theoretical structure, which may thereby obscure the basic simplicity of the model. So we avoid them. Equation (11) can instead be viewed simply as a convenient technical assumption that facilitates an interior solution for b_t.

The firm's first order conditions are the following,

$$b_{t+1} : -\xi_t + E_t\beta\xi_{t+1}[1 + \rho_f - 2\omega b_{t+1}] = 0 \tag{12}$$

$$d_t : \frac{\lambda_t}{\lambda_0} - \xi_t = 0 \tag{13}$$

$$k_{t+1} : E_t\beta\xi_{t+1}[F'_{t+1}(k_{t+1}) - \Phi_k(i_{t+1}, k_{t+1})] - q_t + E_t\beta q_{t+1}(1 - \delta) = 0 \tag{14}$$

$$i_t : \xi_t(-1 - \Phi_i(i_t, k_t)) + q_t = 0 \tag{15}$$

An equilibrium for this model says that the consumer chooses $\{c_t, s_{t+1}\}_{t=0}^{\infty}$ to maximize (2); the firm chooses $\{b_{t+1}, d_t, k_{t+1}, i_t\}_{t=0}^{\infty}$ to maximize (6); and the market for equity determines prices $\{p_t\}_{t=0}^{\infty}$ such that the market clears at $s_t = 1$ for all t. As usual we start by examining the non-stochastic steady state equilibrium. For the current model the key requirement is that k_t is the same for all t. We need to solve for $\{b, c, d, k, i, \lambda, q\}$. Routine algebra gives the non-stochastic steady state solutions as in Uhlig (1999).

Theorem 6.1 *The non-stochastic steady state is characterized by:* $b_{ss} = \frac{\beta(1+\rho_f)-1}{2\beta\omega}$, $k_{ss} = [\frac{(1+a\delta)(1-\beta+\beta\delta)-\beta\frac{a}{2}\delta^2}{A\alpha\beta}]^{\frac{1}{\alpha-1}}$, $i_{ss} = \delta k_{ss}$, $d_{ss} = Ak_{ss}^{\alpha} + (\rho_f - \omega b_{ss})b_{ss} - i_{ss} - \frac{a}{2}\delta^2 k_{ss}$, $c_{ss} = d_{ss}$, $\lambda_{ss} = (c_{ss})^{-\gamma}$, $q_{ss} = \lambda_{ss}[1 + a\delta]$.

The bank account, physical capital and capital investment in terms of exogenous parameters. The expressions for dividends, consumption and the Lagrange multipliers can be easily reduced to expressions in terms of exogenous parameters, by making the obvious substitutions. The expressions have been left as is, in order to highlight the key connections among the variables.

In steady state, the firm's bank account gets larger when the risk free rate ρ_f increases and when the investor cares more about the future. The stronger the impact of empire building ω, the smaller the firm's bank account. The bank account is permitted to be either a positive number or a negative number. So this can be a source of outside financing depending on the parameter values. The choice of physical capital is standard.

Dividends are permitted to be either positive or negative. If the dividend is positive, finance is flowing from the firm to the investor. If the dividend is negative, finance is flowing from the investor to the firm. This depends in a fairly obvious way on returns from real production, leftover physical capital, and the returns on the bank account.

6.3 Quantitative Analysis

We match model generated moments to Compustat firms from 1997 to 2015. The first two moments we want to match are mean and variation of investment rate. We define investment rate as negative investment cash flow over lagged total assets. We use investment cash flow rather than capital expenditure as investment, which is more consistent with our three factor model. We define cash as cash and short-term investments, which is closely linked to the bank account in our model. Net finance is calculated using financing cash flow from cash flow statement. For simplicity, we define net finance as negative dividends, without distinguishing debt and equity financing.

We pick several parameters directly from the literature. Utility curvature γ comes from consumption based asset pricing literature, for example, Campbell and Cochrane (2000). δ is from Hennessy and Whited (2007). We fit our productivity measure using an AR(1) model, getting persistence parameter ρ_z and variance σ_z. Bank baseline rate ρ_f is average one-year treasury yield from 1997 to 2015. Bank Interest rate supply parameter ω is calibrated to match cash/asset.

After setting all parameters, we simulate the model for 5000 time periods, dropping the first 100 observations. Table 10 shows model implied moments and moments calculated using Compustat firms. The model underestimates the variance of investment and average net finance. Similar result is reported in Eisfeldt and Muir (2016), in which model generated average net finance is -0.10.

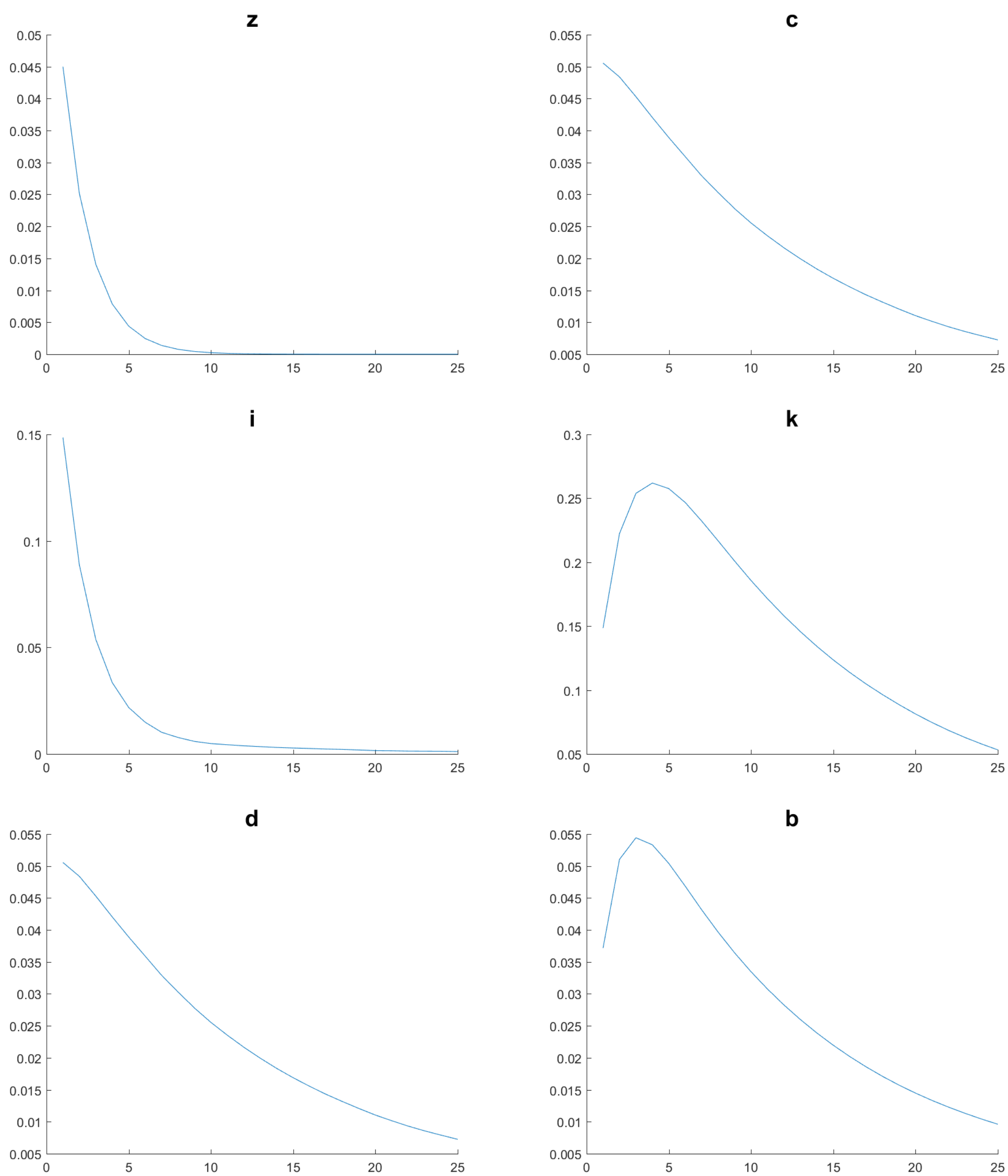
Table 10: Parameter Values

This table presents parameters choice in our model. Utility curvature γ comes from consumption based asset pricing literature, for example, Campbell and Cochrane (2000). δ is from Hennessy and Whited (2007). For each firm i, we fit an AR(1) model, $z_{i,t} = \rho_i z_{i,t-1} + \varepsilon_{it}$, where $\varepsilon_{it} \sim N(0, \sigma_i^2)$. Productivity persistence ρ_z and the conditional standard deviation σ_z match average estimated ρ_i and σ_i. A is normalize to be one. Discount factor β, production technology α, and the adjustment cost a are calibrated jointly to match mean and variance of investment rate, and average net finance. The risk-free interest rate ρ_f is the average one-year Treasury rate from 1997 to 2015. Bank interest rate supply parameter ω is calibrated to match cash/asset.

Panel A: Parameters		
Description	Value	Justification
Set Parameters		
Utility curvature	$\gamma = 2.00$	Campbell and Cochrane (2000)
Depreciation rate	$\delta = 0.1$	Hennessy and Whited (2007)
Productivity parameter	$A = 1$	Scaled
Calibrated Parameters		
Bank interest rate supply	$\omega = 0.0001$	Match Cash
Adjustment cost	$a = 1$	Match Investment
Discount factor	$\beta = 0.974$	Match Investment and NetFinance
Production technology	$\alpha = 0.68$	Match Investment and NetFinance
Risk-free interest	$\rho_f = 0.03$	Match average 12-month treasury bill
Persistence productivity	$\rho_z = 0.559$	Match productivity persistence
Std. Dev. of productivity	$\sigma_z = 0.045$	Match productivity volatility
Panel B: Moments		
	Data	Model
Calibrated		
Average investment/assets	0.093	0.100
Variance of investment/assets	0.114	0.00003
Average cash/assets	0.10	0.10
Average NetFinance/assets	-0.01	-0.09
Other		
Corr(Productivity/assets, NetFinance/assets)	-0.17	-0.75

Figure 5: Impulse Response

This figure shows the impulse response of consumption (c), capital (k), investment (i), dividend (d), and bank account (b) after one standard deviation positive productivity shock (z). The model setup can be found in section 6. The model parameters are calibrated as in Table 10. X-axis displays years after the shock and y-axis displays change relative to the steady state value.



6.4 Impulse Response

The impulse responses are generated by a one standard deviation positive productivity shock. Because the shock process is autoregressive as shown in the top part of 5 it gradually reverts to the long run mean of zero. Most of the impact is in the first few years. By 10 years the shock is essentially gone. But the impact on the economy is not yet gone.

Because of the shock, the firm can generate more revenue and therefore increases capital as quickly as it can. As the shock dies off, the firm permits the capital to also gradually decline. But the decline in the stock of capital takes much longer than the decline of the shock.

Because the firm is more valuable, the firm owner/investor wants to consume more. Consumption jumps right away, and then continues to increase more gradually for the next 3 or 4 years. After that, consumption very gradually declines to the long run mean. But this decline is even slower than the decline in capital. It reflects the fact that the investor discounts the future, but also attempts to smooth consumption. How does the investor manage to increase consumption? The wage did not change, so the investor must be getting more money from the firm. This can be seen in the bottom left hand panel of 5. The flow of resources from the firm d necessarily matches the consumption pattern over time.

The explanation so far seems to create a puzzle. When the positive shock hits the firm invests more and the firm also pays out more. For both of these to happen at the same time, something else has to make up the difference. In our model that is the bank account. The firm has internal financial resources and it uses them in this circumstance. As can be observed in the lower right hand panel of 5 the bank account initially turns sharply negative when the positive productivity shock arrives. The firm is using these resources to satisfy the investor's consumption desires and the investment needs initially. After about 3 years the immediate buffering effect is no longer required, and so the firm very gradually rebuilds the bank account. That rebuilding process happens very slowly.

It is well known that firm level capital and financing are highly persistent, see Lemmon et al. (2008) and DeAngelo and Roll (2015). It is noteworthy that persistence emerges from our model despite the absence of an explicit capital adjustment cost function. Instead the desire of the investor to smooth consumption generates significant persistence in our model.

7 Conclusion

Investors want to make good investments, and high productivity firms might have more of these projects than do other firms. So a natural conjecture is that finance flows to high productivity firms. We show that this natural conjecture is not correct. In order to do this the first part of the paper provides and validates a new measure of firm level productivity, which is easy to apply and has a straightforward interpretation.

Using this productivity measure we establish three key facts. First, the answer to the question in the title is: no. Finance does not generally flow to high productivity firms. It flows away from them. Second, high productivity firms invest more. Third, high productivity firms have reduced financial assets or cash.

In order to explain the facts we provide a simple model. Consider a firm that has a transitory positive productivity shock. The firm needs to invest rapidly to exploit the temporary opportunity. Hence, firm investment increases. The investors discount the future, and so they want the firm to pay out money promptly when it has the funds. Hence, there is a flow of resources from the firm to the investors in response to the shock. But, there is a feasibility constraint on the firm. In order for the firm to do both of these things at the same time, financial resources have to come from somewhere. They come from reduced holdings of financial assets by the firm.

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A Appendix: Variable Construction Details

This appendix provides details on data construction and variable definitions.

A.1 Definitions

For reference several accounting definitions should be kept in mind. These definitions are from Compustat/WRDS.

Net Sales Variable Name = SALE "This item represents gross sales (the amount of actual billings to customers for regular sales completed during the period) reduced by cash discounts, trade discounts, and returned sales and allowances for which credit is given to customers, for each operating segment. Differences, which exist between the data as reported by the company and the Compustat definition, will be indicated by a footnote."

Income Taxes - Total Variable Name = txt "This item represents all income taxes imposed by federal, state and foreign governments."

XSGA – Selling, General and Administrative Expense

COGS is as follows: "U.S. and Canadian GAAP Definition. This item represents all costs directly allocated by the company to production, such as material, labor and overhead. The total operating costs for non-manufacturing companies are considered as cost of goods sold if a breakdown is not available. This item includes the following expenses when broken out separately. However, if a company allocates any of these items to selling, general and administrative expenses, Standard & Poor's will not include them in Cost of Goods Sold." A list of 29 items and then 10 exclusions follow.

Property, Plant and Equipment - Total (Net) Variable Name = ppent is defined as "This item represents the cost, less accumulated depreciation, of tangible fixed property used in the production of revenue. This item is a component of Assets Total (AT)."

Property, Plant and Equipment - Total (Gross) Variable Name = ppegt is defined as "This item represents the cost and/or valuation of tangible fixed assets used in the production of revenue. This item is a component of Property, Plant and Equipment (Net) Total (PPENT)."

AT. "This item represents the total assets/liabilities of a company at a point in time. If the company does not report a useable amount, this data item will be left blank."

Depreciation and Depletion (Cash Flow) Variable Name = depc "This item represents non-cash charges for obsolescence and wear and tear on property, allocation of the current portion of capitalized expenditures, and depletion charges."

Employees Variable Name = EMP "This item represents the number of people employed by the company and its consolidated subsidiaries in thousands."

Capital is measured using Compustat as gross property, plant, and equipment (PPEGT) deflated by price deflator for investment following İmrohoroğlu and Tüzel (2014). Average age of capital stock is (PPGET - PPENT)/DP, which is equivalent to DPACT/DP, total depreciation divided by current depreciation. Age of capital is smoothed by taking 3-year moving average and then rounded to nearest integer. Then capital is deflated according to price index of its average year (fyear - age). In our panel, capital is lagged by one year to measure the available capital at the beginning of the fiscal year.

Labor is calculated by multiplying the number of employees from Compustat (EMP) by average wages from the Social Security Administration).

The following variables are all defined using contemporaneous items from Compustat, unless otherwise specified.

Output = SALE

Valueadded = SALE - (SALE - OIBDP - LABOR)

Book Leverage = (DLTT + DLC)/AT

Market Leverage = (DLTT + DLC)/(PRCC_F*CSHPRI + DLTT + DLC + PSTKL - TXDITC)

Market to Book =(PRCC_F*CSHPRI + DLTT + DLC + PSTKL - TXDITC)/AT

Tangibility = PPENT/AT

Profitability = OIBDP/AT

Dividend = DVT != 0

CASH = CHE/ AT_{t-1}

NET CASH = (ACT - LT)/ AT_{t-1}

Net Finance = FINCF/ AT_{t-1}

Net Finance(DivAdj) = (DLTIS - DLTR + DLCCH + SSTK - PRSTKC - DV)/ AT_{t-1}

Net Finance(Issuance) = (DLTIS - DLTR + DLCCH + SSTK - PRSTKC)/ AT_{t-1}

Debt Δ Book = $\Delta_{t,t-1}$(DLTT + DLC) / AT_{t-1}

Debt Δ Book(CashAdj) = $\Delta_{t,t-1}$(DLTT + DLC - CHE) / AT_{t-1}

Debt Net Sales = (DLTIS - DLTR + DLCCH)/ AT_{t-1}

Equity Δ Book = $\Delta_{t,t-1}$(AT - LT - PSTKL + TXDITC + DCVT) / AT_{t-1}

Equity Δ Market = $\Delta_{t,t-1}$(PRCC_F $\times$ CSHPRI) / AT_{t-1}

Equity Net Sales = (SSTK - PRSTKC)/ AT_{t-1}

Table 11: Data Cleaning Steps

We start with COMPUSTAT/CRSP Merged Fundamentals Annual data file from 1950 to 2015. We choose consolidation level "C". Industry Format "INDL" and with format "STD". We keep data with the link type "LC" and "LU". We partition the sample into training sample and test sample. We choose 90% of firms within each two-digit SIC industry as training sample. The rest firms are in test sample.

		No. of observations.
Start	COMPUSTAT/CRSP Fundamentals Annual Merged 1950 to 2015	286,095
keep	keep if datafmt == "STD"	0
keep	keep if indfmt == "INDL"	0
keep	keep if Foreign Incorporation Code =="USA"	-23809
drop	Drop if sic>=6000 & sic<=6999 or sic >=4900 & sic<=4999 Exclude financial firms and regulated utilities	-70871
drop	drop duplicates firm-year observation	-1724
keep	keep if 1970 <= fyear <= 2015	-14592
drop	drop if Average Market Leverage <0.05	-29534
drop	At least 10 Years nonmissing leverage	-31166
drop	drop if assets or gvkey is missing, drop	-109
End	Cleaned Data	114,290

Sample Partition

Manufacturing firms are defined as two digit SIC $\geq$ 20 and $\leq$ 39

	1970-2015	No. of observations.
Start	Cleaned Data	114,290
training	randomly keep 90% of firms within each industry	101,140
testing	the rest firms are test sample	12,073
All	the rest firms are test sample	114,290

Variable Construction

We drop observations in 1970, 1971 because capital is defined as the inflation -adjusted ppegt.

	1972-2015	No. of observations.
Training	50,993 manufacturing firm-year, 40,591 non-mfg.	91,584
Testing	5,912 manufacturing firm-year, 4,835 non-mfg.	10,747
All	56,905 manufacturing firm-year, 45,426 non-mfg.	102,747